Nonstandard Risky-Choice Framing Effects with Somewhat Risky Options: Explorations and Theory Comparisons

Research Thesis

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Abstract

When people are faced with a choice between a sure option (e.g., *200 people will be saved*) and a risky option (e.g., *1/3 probability that 600 people will be saved and 2/3 probability that none will be saved*), they tend to choose the sure option in the gain frame (e.g., the verb "*save*" is used) and the risky option in the loss frame (e.g., the verb "*die*" is used). This difference is the standard risky-choice framing effect (Tversky & Kahneman, 1981). However, very few studies of this effect have used "somewhat risky" (SR) options in which the outcomes are not all-or-none. Additionally, different theories (e.g., Prospect Theory, Fuzzy-Trace Theory, Explicated Valence Account, Sentiment Analysis) make different predictions for framing effects in some choices involving SR options. In our study, the option pool included 4 SR options, a sure option, and an all-or-none risky option. The SR options differed in whether there was a zero outcome (e.g., *none saved*) in one frame and whether the probabilities matched those in the risky option. 15 option pairs and 2 frames yielded 30 cells (between-subjects), each with 4 domains (e.g., disease, investment; within-subjects). We obtained participants through OSU's Research Experience Program (REP) (N =887) and MTurk (N=946). For our analysis, we used mixed-effects logistic regression and fit separate models for individual theories. We found that Sentiment Analysis (a text-based account) fit best for the REP sample, whereas Prospect Theory (a mathematical model that involves weighting one's utilities for the possible outcomes) fit best for the MTurk sample. However, none of the theories predicted framing effects very accurately in our expanded choice set. There was almost always a significant residual framing effect and substantial unexplained variation in choice proportions. These results suggest that people might not apply a consistent set of principles across all choice pairs, but instead apply different decision-making strategies in different situations.

Keywords: framing effects, prospect theory, somewhat risky options

Introduction

Several times people have to make decisions for choices that involve risk, e.g., choosing an insurance plan or buying stocks. There is always some uncertainty involved in the stock market. How do people decide which stocks to buy or sell? Or they might have to choose between two treatments for diabetic foot: dressing and amputation. Dressing the foot does not guarantee that it will be healed. If the wound festers, amputation is required for a bigger area. So, some people choose to undergo amputation directly. Hence, risk can also be involved while choosing a medical procedure. It is interesting to understand how people perceive the risk of the alternatives and respond while making these choices. These types of questions are typically studied by presenting participants with gambles and asking them to make choices. Multiple theories have been developed to explain the observations in risky-choice decision making. One effect which is observed in the studies involving risk is the framing effect. The evidence for framing effects was first collected when Prospect Theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981) was introduced as an improvement to the widely accepted Expected Utility Theory (Savage, 1954; von Neumann & Morgenstern, 1944).

Consider the traditional Asian Disease Problem (Tversky & Kahneman, 1981) in the original wording where the participants had to choose between the two alternatives of whichever of the two problems was presented to them:

> Imagine that the U.S. is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequences of the program are as follows:
>
> *Problem 1:*
>
> If Program A is adopted, 200 people will be saved.
>
> If Program B is adopted, there is a 1/3 probability that 600 people will be saved, and 2/3 probability that no people will be saved.

Which of the two programs would you favor?

Problem 2:

If Program C is adopted, 400 people will die.

If Program D is adopted, there is a 1/3 probability that nobody will die, and 2/3 probability that 600 people will die.

Which of the two programs would you favor?

Alternatives A and C are characterized as the “sure” options because there is a 100% probability of the event occurring. Since B and D have probabilities which are not 1, there is risk involved and so they are called the “risky” options.

Most people chose Program A in problem 1, whereas most people chose Program D in problem 2. If we look closely, we observe that A and C are equivalent, as are B and D. The difference between the problems is that “save” is used in problem 1 and “die” is used in problem 2. This different preference for the options based on the framing is the risky-choice framing effect.

Expected Utility Theory states that each person has a utility function for the total quantity of a thing (e.g., wealth). For most people, this function is concave with diminishing marginal utility. An increase or decrease in the quantity of interest (e.g., dollars) causes the value to move up or down along the same function. As the two framings of the problem are effectively equivalent, people should not change their preference of the options based on the framing. However, contrary to the prediction by the Expected Utility Theory, a reversal is observed.

Prospect theory accommodates for these observations by differentiating between the Gain frame and the Loss frame. It also proposes that an implicit reference point is created in the mind depending on which frame is used. Problem 1 falls under the Gain frame because it contains the word “save”, which results in the implicit reference point becoming “*none are saved*”. Problem 2 is in the Loss frame since it contains “die” which makes “*none die*” the reference point.

Figure 1 shows the hypothetical value function (with an exaggerated shape) as put forth by the Prospect Theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). The theory states that most people are risk-averse in the Gain frame, shown by the concave shape. Also, people tend to be risk-seeking in Loss frame (convex shape). A value function for a person who has no risk-aversion or risk-seeking would be a straight line with a positive slope. Risk-aversion implies a greater preference for the sure option (A in the gain frame) and risk-seeking means a greater preference for the risky option (D in the loss frame). Hence, Prospect Theory explains the standard framing effect.

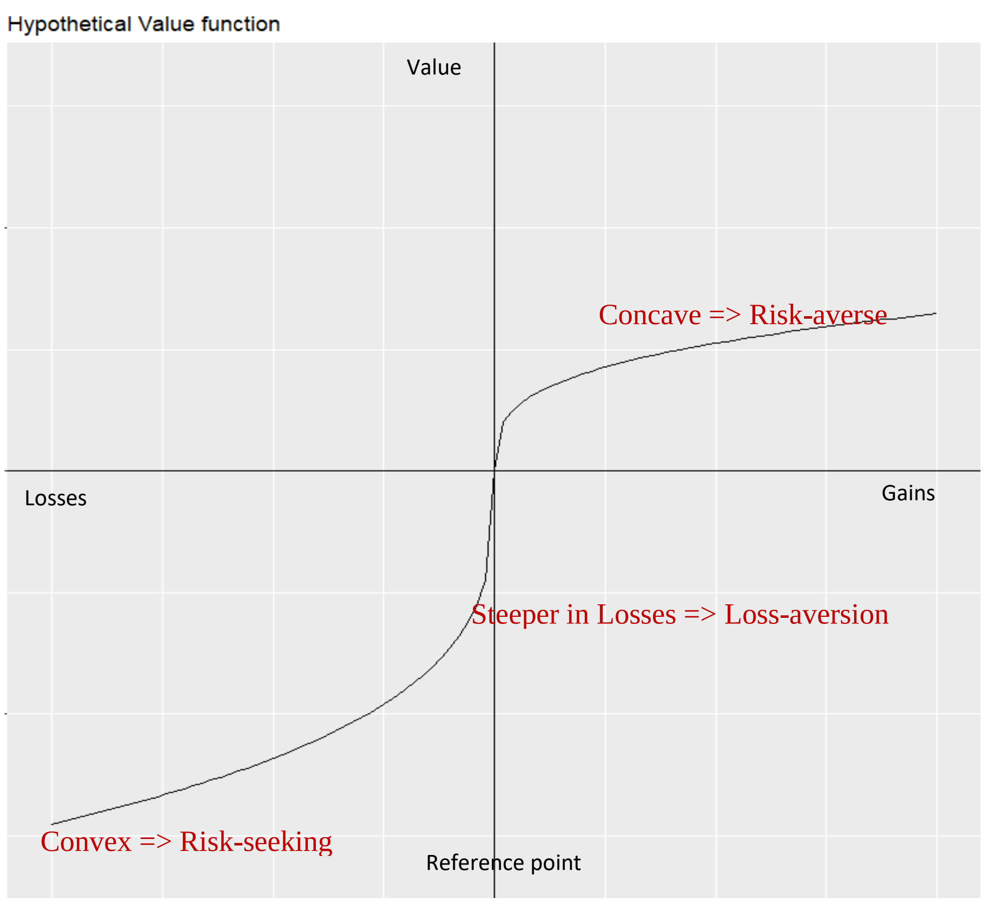


Figure 1

Prospect Theory also has the components of loss aversion and non-linear probability weighting. Loss aversion refers to a steeper slope of the value function in the loss frame than in the gain frame. It means that people dislike a loss more than they like a gain of the same quantity. In addition, the theory states that low probabilities are overweighted and moderate and higher probabilities are underweighted. The framing effect problem was not created to test these parts of the theory.

The above example only contains sure and risky options. However, it is possible to create somewhat-risky options and check whether this effect is observed with the new cases. This expanded option pool can also be used to test the generalizability of Prospect Theory and other competing theories.

Somewhat risky options

Observe that in a standard risky option in the gain frame ”*1/3 probability that 600 people will be saved*” is the outcome with the highest extreme value (since the total number of people in the story is 600). Whereas “*2/3 probability that no people will be saved*” outcome contains the lowest extreme value i.e., zero (no people). There are many ways to construct an option where either one or both of the outcome endpoints are pulled in towards the midpoint. E.g., “*1/3 probability that 450 people will be saved and 2/3 probability that 75 people will be saved*” (Miller & Fagley, 1991). Here the endpoints are not present anymore, the probabilities match those in the standard risky option, and the expected value is the same as the standard sure and risky options. This is an example of a Somewhat-risky option (specifically *Somewhat-Risky Matched*, as we will define later). The details of all the option types we used are included in the **Methods *Stimuli*** section.

Significance of this study

There has been limited research on framing effects with somewhat risky options (e.g., Schneider, 1992; Tombu & Mandel, 2015). Also, multiple theories have been proposed over the years for explaining framing effects (e.g., Fuzzy-Trace Theory, Explicated Valence Account). Although all these theories correctly predict the standard framing effect, their predictions differ for some comparisons when somewhat-risky options come into the picture. This study aims to bridge the gap in the literature by (a) inspecting framing effects with some unexplored somewhat-risky options, and (b) testing and finding how well the theories of risky choice generalize for framing effects across the expanded choice set.

Theories and Accounts

In this section, we will review all the theories and accounts we compared in our study.

Prospect Theory

We used four versions of Prospect Theory for our comparisons:

1. **Full Prospect Theory.** The parameter values for this version were taken from Tversky and Kahneman (1992). The power in the value function for gains (α) and for losses (β) are both 0.88. Loss aversion parameter (λ) is 2.25, implying steeper slope in losses than gains. Probability weighting in gains (γ) is 0.61 and in losses (δ) is 0.69, implying the usual non-linear probability weighting pattern.

Since loss aversion and non-linear probability weighting do not typically play a role in the explanations of framing effects, we decided to test simpler versions of the theory by removing these parameters.

2. **Prospect Theory without loss aversion**. We fixed λ to 1 to eliminate loss aversion. This implies that the slope in losses is no longer steeper than in gains. Other parameters were the same the full Prospect Theory.
3. **Prospect Theory without weighting parameters**. Next, we removed the weighting of the probabilities by setting $\gamma = \delta = 1$. This made the probability weighting function linear. Other parameters were the same as the full Prospect Theory.
4. **Prospect Theory without loss aversion or weighting parameters**. In this plain version of Prospect theory, we removed both loss aversion and probability weighting ($\lambda = 1$, $\gamma = 1$, $\delta = 1$) from the full version. The only feature of Prospect Theory remaining here is the risk-aversion (concave value) in gains and risk-seeking (convex value) in losses relative to reference points.

To obtain standardized predictions from each version of this theory, we input the above parameter values in the Cumulative Prospect Theory score calculator for each option (Köbberling, 2002). Since all our options have at most 2 outcomes, Cumulative Prospect Theory and Prospect Theory yield the same prospect score. Then we coded each option pair as the difference between the less risky option and the more risky option (PT[less risky]-PT[more risky]) and standardized option pairs across domains by dividing the difference by the magnitude of the domain (e.g., the number of lives at stake) raised to the 0.88 power.

Fuzzy-Trace Theory

Fuzzy-Trace Theory (Reyna & Brainerd, 1991, 1995) states that people look at the gist and verbatim of the options separately while making a choice. Gist is the essence or understanding of the meaning whereas verbatim is the exact numerical (mathematical) representation of the option. People rely on the simplest gist representation which helps them distinguish between options. There are three types of comparisons under Fuzzy-Trace Theory (Broniatowski & Reyna, 2018)-

1. Categorical: In this case, the choices are classified into categories (e.g., “some saved” vs. “none saved”) and the categories are compared. These are the categorical translations of the options in our example:
    a. Sure option: “*200 people will be saved*” becomes “Some are saved”.
    b. Risky option: “*1/3 probability that 600 people will be saved and 2/3 probability that no people will be saved*” becomes “Some are saved or none are saved”.
    c. Somewhat-Risky Matched option: “*1/3 probability that 450 people will be saved and 2/3 probability that 75 people will be saved*” becomes “Some are saved or some are saved”.

According to the categorical representation (Reyna, 2012), in the gain frame the Sure option will be preferred over the Risky option, as the Risky option contains the “none are saved” part. In the Somewhat-Risky Matched vs. Risky comparison, the Somewhat-Risky Matched option will be preferred as it contains “some are saved” in the second outcome against the “none are saved” in the Risky option. However, for the Sure vs. Somewhat-Risky Matched pair, there will be no preference because neither of the two options contains “none are saved” to make it worse than the other. Hence, for Sure vs Somewhat-Risky Matched, the categorical comparison from Fuzzy-Trace Theory predicts no preference.

2. Ordinal: In this comparison, words like ‘fewer’ and ‘more’ are used within the same category (i.e., compare ‘some’ parts from one option to ‘some’ or ‘none’ parts from the other option).
    a. Risky option: “*1/3 probability that 600 people will be saved and 2/3 probability that no people will be saved*”-

i. "Less chance that more are saved and more chance that none are saved".

b. Somewhat-Risky Matched option: "*1/3 probability that 450 people will be saved and 2/3 probability that 75 people will be saved*"-

i. "Less chance that some are saved and more chance that fewer are saved".

In the choices we will consider, the ordinal comparison will never matter. Also since the expected values of all our options are the same, a better outcome on the higher end is offset with a worse outcome on the lower end for each of the options. Hence, it is not possible to distinguish between the options in our choice pool using this comparison. Subsequently, we do not use ordinal representation while coding our options.

3. Interval (verbatim): If the previous two comparisons do not yield a clear decision, the expected values of the options help in making the decision. However, we do not use interval representation while coding our options since all our options have the same expected value.

Unlike Prospect Theory where the coding of the pairs has continuous values obtained from a function of the difference between the less risky option and the more risky option, the Fuzzy-Trace Theory has discrete values. The pairs are coded "1" in the less risky option is preferred according to the theory, "0" when there should not be a preference, and "-1" in the more risky option would be preferred by the participant. Since Fuzzy-Trace Theory doesn't say anything about the magnitude of the categorical difference, we use unit differences for the codes.

Explicated Valence Account

According to the Explicated Valence Account, people pay attention to the explicated outcome valence (the goodness or badness) of the options while making decisions (Tombu & Mandel, 2015). For the traditional sure option in the gain frame, people being saved is a good thing, so the sure option has a positive valence. On the other hand, the risky option as a positive part ("*600 will be saved*") and a negative part ("*none will be saved*"). Hence, the valence of the risky option is mixed. Therefore, the sure option is preferred over the risky option in the gain frame, as positive is better than mixed. In the loss frame, the sure option has negative valence ("*400 people will die*"), but the risky option has mixed valence (positive for "*none will die*" and negative for "*600 will die*"). Hence, the risky option is preferred in the loss frame as mixed valence is more desirable than negative valence.

When we consider the somewhat-risky matched choice, the "*450 will be saved*" part has positive valence and the "*75 people will be saved*" part also has positive valence. Hence, people would have no preference between the sure and somewhat-risky matched options in the gain frame because both options have the same valence. Furthermore, they would choose both of these options over the risky option. Similarly, the sure and somewhat-risky matched options will both have a negative valence in the loss frame and will be less preferred as compared to the risky option which will have a mixed valence (Tombu & Mandel, 2015). This absence of preference between the sure and somewhat-risky matched options is contrary to what Prospect Theory predicts for comparisons involving somewhat-risky matched options.

We coded the option pairs as "1" if the less risky option would be preferred, "0" for no preference, and "-1" if the more risky option would be preferred. Incidentally, the option pair coding from Explicated Valence Account turns out to be the same as Fuzzy-Trace Theory for the stimuli in our study (though this is not always the case for other types of option pairs).

Sentiment Analysis

Sentiment Analysis is a natural language processing technique which assigns a positive, negative, or neutral value to some text by processing it for negators, intensifiers, de-amplifiers, etc. Exactly which aspects of the text are processed, and which coding scheme is used depends on the specific sentiment analysis tool. We can say that this technique focuses on the "gist" of the sentence as it only analyses the text and does not take numbers into consideration (Wall, Crookes, Johnson, & Weber, 2020). For predictions from Sentiment analysis, we obtained the sentiment value for each option using the sentiment() function from the *sentimentr* package in R (Rinker, 2019) and assigned the difference between the less risky option and more risky option to each option pair. If we obtain the sentiment of the three options in the gain frame of our example, the sure option has a score of 0.4, the risky one has 0, and the somewhat-risky matched option scores 0.44. Hence, this account predicts that the somewhat-risky matched option is preferred over the risky option and slightly preferred over the sure option in the gain frame. It also says that the sure option is preferred over the risky one, as in the standard framing effect. In the loss frame for this example, the risky option is preferred over the other two options, and the sure option is preferred over the somewhat-risky matched option.

More accounts

In a previous meta-study in the DeKay lab (DeKay, Rubinchik, & De Boeck, 2019; Rubinchik, 2019), the researchers found that there was an enhanced framing effect in the Somewhat-Risky Matched vs. Risky comparison than in the traditional Sure vs. Risky comparison. This result was not exactly predicted by any of the theories mentioned above, though Sentiment Analysis would predict a small increase in the effect size. Hence, we defined a couple additional accounts to possibly explain these results.

1. **Fuzzy-Trace Theory +.** This modified version of Fuzzy-Trace Theory predicts a higher framing effect in comparisons with matching outcome probabilities, as it suggests that the matched probabilities will make the options more “alignable” and draw more attention to the categorical comparison between the zero and non-zero outcomes. Consider the somewhat-risky matched vs. risky option from our example. The first parts “*1/3 probability that 450 people will be saved”*(Somewhat-risky matched) and “*1/3 probability that 600 people will be saved*” (Risky)

have matching probabilities and both translate to "some are saved". The second parts of the options *"2/3 probability that 75 people will be saved*" (Somewhat-risky matched) and *"2/3 probability that no people will be saved*" (Risky) have matching probabilities (e.g., 2/3). The matching probabilities might draw attention to this "some" vs. "none" comparison, resulting in an enhanced framing effect when compared to the standard effect in sure vs. risky. Several articles (e.g., Reyna, 2012; Reyna & Brainerd, 1995) have made similar arguments for other types of framing questions. Hence, Fuzzy Trace Theory + also includes the coed -2 and +2 for the predictions.

2. **Good/Bad Count.** This is a modified version of Explicated Valence Account which states that an option with two positive outcomes will appear better than an option with one positive outcome. And two negative outcomes will appear worse than a single negative outcome (in loss frame). So, the difference between somewhat-risky matched vs. risky will seem larger than between sure vs. risky. Hence, the framing effect size will be bigger for these comparisons. Therefore, the predictions would be coded as +2 (or -2) in these types of comparisons.

Study

Method

Participants. We used Qualtrics to collect responses for the study. 1138 undergraduate introductory psychology students (M_{age} = 19 years, 62% females) were recruited through the OSU REP system. To validate our findings, we replicated the study using a non-student sample from MTurk with 1024 participants (M_{age} = 40 years, 51% females). This sample size was determined by considering about 30 participants for each of the 30 cells (details in the ***Stimuli*** section).

Stimuli. There were 30 cells in the study. A pool of 6 types of options with varying degrees of riskiness was used to construct the cells. The options below are ordered in an increasing order of riskiness based on the utility function $U(x) = x^{\alpha}$ for any α between 0 and 1 in the gain frame (Schneider, 1992). To illustrate the 6 options, we will use the cancer domain.

> ***Scenario:*** The National Cancer Institute has two possible treatment programs for a rare form of skin cancer that has affected 9,000 people in the country. There are adequate resources to implement only one of the two treatment programs.

[Option Pool for Gain frame in Cancer Domain]

1. ***Sure option:*** 3,600 patients will be saved.
   - Traditional sure option (Tversky & Kahneman, 1981)
2. ***Somewhat-risky mismatched option:*** There is a 1/4 probability that 7,500 patients will be saved and a 3/4 probability that 2,300 patients will be saved.
   - The term 'Mismatched' means that the probabilities do not match those in the *Risky* option, number 6.
3. ***Somewhat-risky matched option:*** There is a 2/5 probability that 6,300 patients will be saved and a 3/5 probability that 1,800 patients will be saved.
   - The term 'Matched' means that the probabilities match those in the *Risky* option, number 6.
4. ***Somewhat-risky zero-in-loss option:*** There is a 1/4 probability that 9,000 patients will be saved and a 3/4 probability that 1,800 patients will be saved.
   - This option contains the larger endpoint outcome (i.e., 9000) but not the smaller endpoint (i.e., 0) in the Gain frame. In the Loss frame, there is a 1/4 probability that no patients will die. It is analogous to the Schneider's (1992) 25/75 option.

5. ***Somewhat-risky zero-in-gain option:*** There is a 3/5 probability that 6,000 patients will be saved and a 2/5 probability that no patients will be saved.
    - This option contains the smaller endpoint outcome (i.e., 0) but not the larger endpoint (i.e., 9000) in the Gain frame. In the Loss frame, the larger endpoint (i.e., 9000) is present. It is analogous to the Schneider's (1992) 75/25 option.
6. ***Risky option:*** There is a 2/5 probability that 9,000 patients will be saved and a 3/5 probability that no patients will be saved.
    - The traditional all-or-none risky option (Tversky & Kahneman, 1981). It is also analogous to the Schneider's (1992) 50/50 option.

The options had the same expected value but differed in the probabilities and outcomes. Each condition included one pair of these options. There were 6 x 5 / 2 = 15 pairs in the gain frame and 15 corresponding pairs in the loss frame, for a total of 30 pairs (cells). Further information on the construction of options is given in the **Appendix**.

Procedure. Each participant was assigned to one of the 30 cells. Regardless of condition, each participant was asked to make four choices, one in each of four domains (wildfire, drought, investment, and cancer), in random order. For each choice, the participants also had to indicate their preference on a 7-point scale with endpoints labeled 'Strong Preference for A [or B]' and the midpoint labeled 'No Preference at All'. *Figure 2* is an example from the Wildfire domain (based on Peters & Levin, 2008).

Imagine that the wildfire season is about to start and an old-growth forest in the Northwest of the U.S. will be affected. This forest is home to 6,000 animals that are endangered by the fire. Two programs have been proposed to protect the animals:

If Program A is adopted, there is a 2/5 probability that 6,000 animals will be saved and a 3/5 probability that 2,000 animals will be saved.

If Program B is adopted, there is a 3/5 probability that 4,800 animals will be saved and a 2/5 probability that 1,800 animals will be saved.

Which of the two programs would you favor?

Program A	Program B

To what extent do you favor Program A or Program B?

Strong Preference for Program A	Moderate Preference for Program A	Slight Preference for Program A	No Preference At All	Slight Preference for Program B	Moderate Preference for Program B	Strong Preference for Program B

Figure 2

Table 1 contains the stimuli for the gain frame for the remaining three domains.

Table 1

Stimuli values for the Gain frame

Domain	Option	Better outcome	Probability of better outcome	Worse outcome	Probability of worse outcome
Wildfire	Sure	3600	1	0	0
	Somewhat-Risky Mismatched	5400	2/5	2400	3/5
	Somewhat-Risky Matched	4800	3/5	1800	2/5
	Somewhat-Risky Zero-in-Loss	6000	2/5	2000	3/5
	Somewhat-Risky Zero-in-Gain	4800	3/4	0	1/4
	Risky	6000	3/5	0	2/5
Drought	Sure	24000	1	0	0
	Somewhat-Risky Mismatched	42000	1/3	15000	2/3
	Somewhat-Risky Matched	36000	1/2	12000	1/2
	Somewhat-Risky Zero-in-Loss	48000	1/3	12000	2/3
	Somewhat-Risky Zero-in-Gain	36000	2/3	0	1/3
	Risky	48000	1/2	0	1/2
Investment	Sure	24000	1	0	0
	Somewhat-Risky Mismatched	60000	1/5	15000	4/5
	Somewhat-Risky Matched	48000	1/3	12000	2/3
	Somewhat-Risky Zero-in-Loss	72000	1/5	12000	4/5
	Somewhat-Risky Zero-in-Gain	48000	1/2	0	1/2
	Risky	72000	1/3	0	2/3

Exclusion criteria. We excluded participants who finished the task too quickly or too slowly: completion time less than 60 seconds or more than 2.5 SDs above or below the mean completion time after transforming the timings with a Box-Cox transformation, for answering any pair of binary-choice and continuous-preference questions inconsistently (e.g., choosing A but rating B as more preferred) or not answering two or more of the eight choice and preference questions. The final sample size used for analysis was 887 from REP and 946 from MTurk.

Results and Discussion

In the REP sample (*Figure 3*), the less risky option is chosen 87% of the time in the gain frame and 53% of the time in the loss frame. In the MTurk sample (*Figure 4*), the less risky option is chosen 93% of the time in the gain frame and 47% of the time in the loss frame. Hence, overall there is a sizeable framing effect in both samples. There is also a slight preference for the less risky option.

Framing effects across conditions

For each of 15 conditions in gain and loss frames, we computed the proportion of choices in which the less risky option was chosen (*Figure 3, Figure 4*). A framing effect is observed where the gain point (salmon color) is above the loss point (cyan color), which is apparent for most points in the figures.

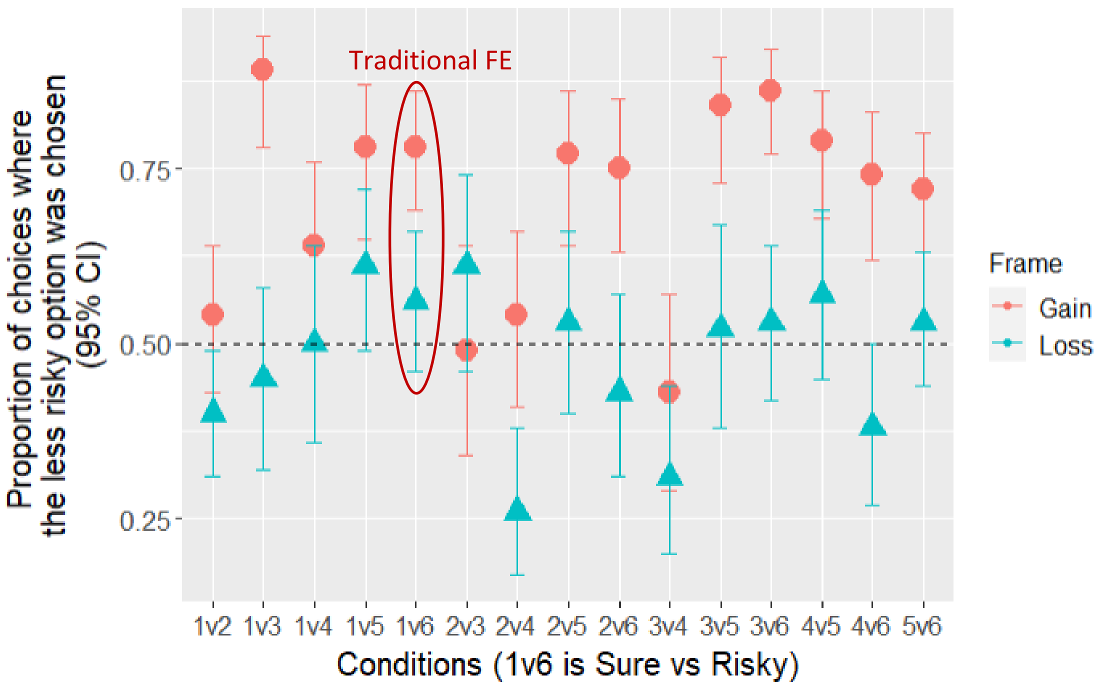


Figure 3. Proportion of choices where the less risky option was chosen in the REP sample is plotted for each of the 15 conditions for gain (salmon) and loss (cyan) frame. Conditions 1v4, 2v3, and 3v4 do not have a significant framing effect.

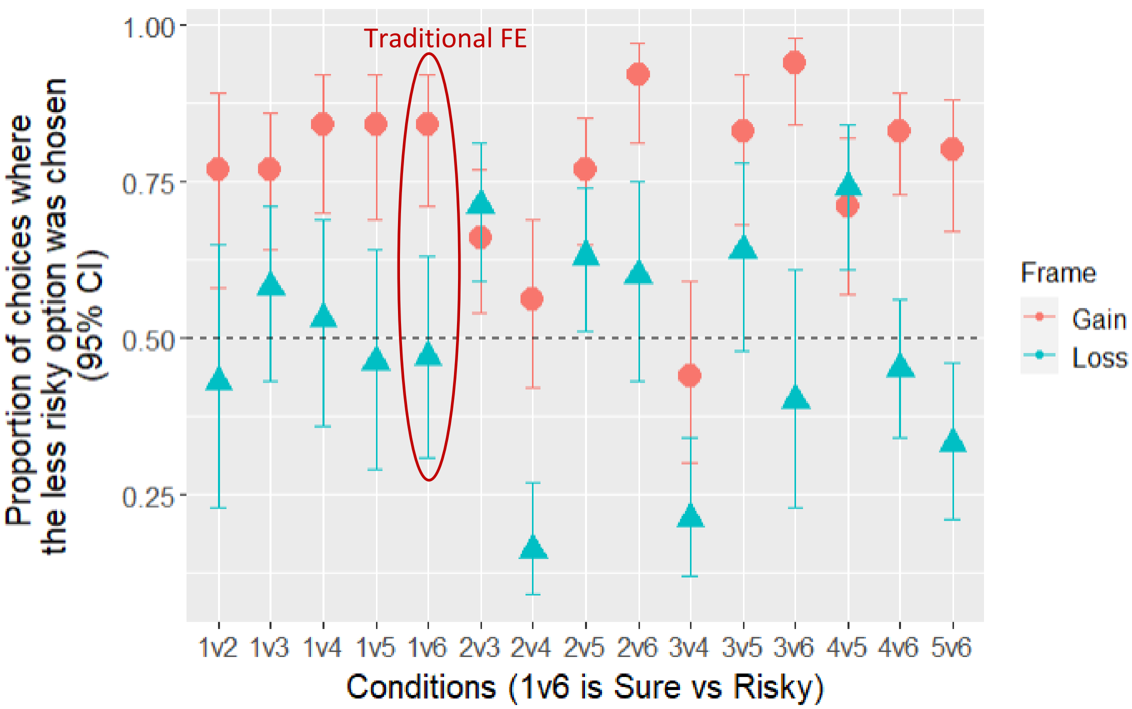


Figure 4. Proportion of choices where the less risky option was chosen in the MTurk sample is plotted for each of the 15 conditions for gain (salmon) and loss (cyan) frame. Conditions 2v3, 2v5, 3v5, and 4v5 do not have a significant framing effect.

Eight of these conditions have been studied previously and 7 are novel conditions. Although it is a laborious process, looking at the conditions separately will enable us to detect any patterns based on theories and connect the results to the previous literature. Regression models considering all the conditions together are presented later. For Prospect Theory and Sentiment Analysis (both of which have continuous predictions), we considered all predictions with the gain and loss coding differences (not to be confused with p-value) less than or equal to .05 as near-zero effects.

I) Previously studied conditions

First, consider the traditional sure vs. risky comparison:

Condition 1v6: Sure vs. Risky

In the traditional Sure vs. Risky condition, the framing effect is observed for both samples. This is consistent with most of the previous literature (e.g., Kühberger, 1998; Schneider, 1992; Tombu & Mandel, 2015; Tversky & Kahneman, 1981).

Condition 1v3: Sure vs. Somewhat-Risky Matched

In the REP sample, we get a framing effect double the size of the standard effect. In the MTurk sample, it is barely significant. The Prospect Theory versions with weighting parameters and Sentiment Analysis both predict a framing effect. The result from the unpublished meta-studies in DeKay Lab (DeKay, Rubinchik, & De Boeck, 2019; Rubinchik, 2019) shows a standard framing effect. Tombu & Mandel (2015) Experiment 1 Same Valence Pattern contains this comparison. They found that there was a non-significant reversed framing effect. Miller and Fagley (1991) found that this comparison had a framing effect of roughly the standard size. van der Pligt & van Schie (1990) also obtained a typical effect in their oil-production problem.

Condition 1v4: Sure vs. Somewhat-Risky Zero-in-loss

This condition has a non-significant framing effect in the REP sample, but a slight significant effect in the MTurk sample. Schneider (1992) also found that the Sure vs. 25/75 comparison yielded no sizeable framing effect. However, the majority of the participants were risk-seeking in both of her frames.

Condition 1v5: Sure vs. Somewhat-Risky Zero-in-gain

In this condition, the framing effect has a standard size in the MTurk sample, but is barely significant in the REP sample. On the other hand, Schneider (1992) found that the Sure vs. 75/25 comparison had a prominent framing effect. None of the theories predict a larger than standard framing effect. van der Pligt & van Schie (1990) found a regular sized effect when lives were at stake, but smaller for other domains like time and money.

Condition 3v6: Somewhat-Risky Matched vs. Risky

The effects in both the samples are larger than the standard effect in the respective samples. This is a replication of the result obtained in the unpublished meta-studies from the DeKay Lab (DeKay, Rubinchik, & De Boeck, 2019; Rubinchik, 2019) where the effect size was twice as big. The magnitude is best predicted by Fuzzy-Trace Theory + and Good/Bad Count.

Condition 4v5: Somewhat-Risky Zero-in-loss vs. Somewhat-Risky Zero-in-gain

The MTurk sample shows a non-significant reversal and is consistent with all the theories' predictions of near-zero effects. But none of the theories predict the small significant framing effect seen in the REP sample. Overall, there is a preference for the *Somewhat-Risky Zero-in-loss* (less risky) option in both frames. Schneider (1992) found a significant framing effect in most domains for this condition (25/75 vs. 75/25). But her data also shows a general preference for the less risky option, which aligns with our results.

Condition 4v6: Somewhat-Risky Zero-in-loss vs. Risky

A larger-than-standard framing effect is observed in the REP sample and a standard sized effect is present in the MTurk sample. All theories except Prospect Theory without loss aversion or weighting parameters (which predicts near-zero effect), correctly predict the direction but not the enhanced magnitude of the effect. In Schneider's study (1992), there was a general preference for the less risky (25/75) option in both frames, and thus smaller framing effects in most domains. But in our data, we observe risk-seeking behavior in the loss frame.

Condition 5v6: Somewhat-Risky Zero-in-gain vs. Risky

There is a barely significant framing effect in the REP data but a slightly larger-than-standard effect in the MTurk sample. All theories except Prospect Theory without loss aversion and probability weighting parameters (which predicts a near-zero effect) explain the direction of the effect. Schneider (1992) found almost no framing effect and got a preference for 75/25 (less risky) in both frames. Her findings align with our REP data, but not our MTurk data.

II) Novel Conditions

We have 7 novel conditions in our study (any comparison with *Somewhat-Risky Mismatched* and any comparison with *Somewhat-Risky Matched* paired with a somewhat-risky option with zero in one of the two frames). When the *Somewhat-Risky Mismatched* option (the least risky of the 4 somewhat-risky options) is paired with any other option, we usually observe a significant framing effect. The exception is the comparison *Somewhat-Risky Mismatched* vs.

Somewhat-Risky Matched (2v3) where both samples have a non-significant framing effect as predicted by all the theories.

For *Somewhat-Risky Matched* vs. *Somewhat-Risky Zero-in-loss* (3v4; with the larger endpoint in gains), we see an overall preference for the *Somewhat-Risky Zero-in-loss* (more risky) option. And with *Somewhat-Risky Matched vs. Somewhat-Risky Zero-in-gain* (3v5), there is a general preference for the *Somewhat-Risky Matched* (less risky) option. This preference for the less risky option is also true for *Somewhat-Risky Mismatched vs. Somewhat-Risky Zero-in-gain* (i.e., for 2v5). These results show that people liked the *Somewhat-Risky Zero-in-loss* option and disliked the *Somewhat-Risky Zero-in-gain* option when compared with the somewhat-risky options with no zero outcomes. This is also reflected in the *Somewhat-Risky Zero-in-loss* vs. *Somewhat-Risky Zero-in-gain* (4v5) condition above.

Distinguishing between Theories

We saw a mixed performance of the theories where some theories performed better in some conditions and others performed better in other conditions. Following are a couple of conditions where we can see a distinction in their performance.

In *Sure* vs. *Somewhat-Risky Matched* (1v3), the versions of Prospect Theory with the probability weighting parameters and Sentiment Analysis correctly predict significant framing effects, whereas the more gist-based theories fail as they incorrectly predict non-significant framing.

In *Somewhat-Risky Mismatched* vs. *Somewhat-Risky Zero-in-Loss* (2v4) and *Somewhat-Risky Matched* vs. *Somewhat-Risky Zero-in-Gain* (3v5), all the gist-based theories correctly predict that significant framing effects will be observed. On the other hand, Prospect Theory versions (except the full version) fail to predict this observation. The common thing between these two conditions is that one of the alternatives is a somewhat-risky option with a zero in one of the two frames.

Overall, we can state that Prospect Theory performs better when the risk difference in the options is non-trivial (two somewhat-risky options would have a small difference in the risks) and neither somewhat-risky option has a zero in either frame. When a somewhat-risky option with zero in one of the two frames is involved, the gist-based theories pick up the “some vs. none” difference better.

Regression Models

When we looked at the conditions separately, we observed a variety of results as explained above and it was difficult to compare all the theories to each other. So, we used all the conditions to run mixed-effects logistic regression models to further compare theories.

Model:

$$\text{Logit}(P_{\text{less\_risky}}) = (b_0 + u_{0\text{participant}}) + b_1\text{*theory} + b_2\text{*frame} + b_{3\text{-}5}\text{*domains}$$

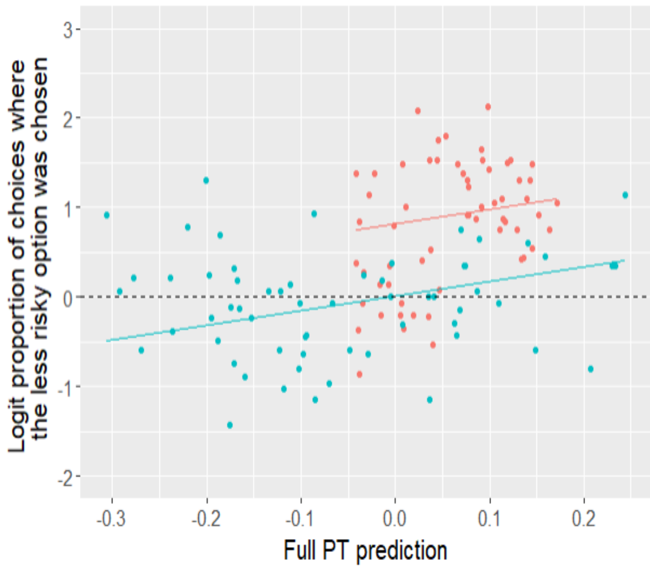
The theory variable in each model is the prediction for each option pair (continuous for Prospect Theory versions and Sentiment Analysis and discrete for the Gist-based accounts) made by the corresponding theory (explained previously in **Theories and Accounts**). Gain frame is coded as positive (0.5) and loss as negative (-0.5). The domain variable is a 4-level categorical variable.

Table 2

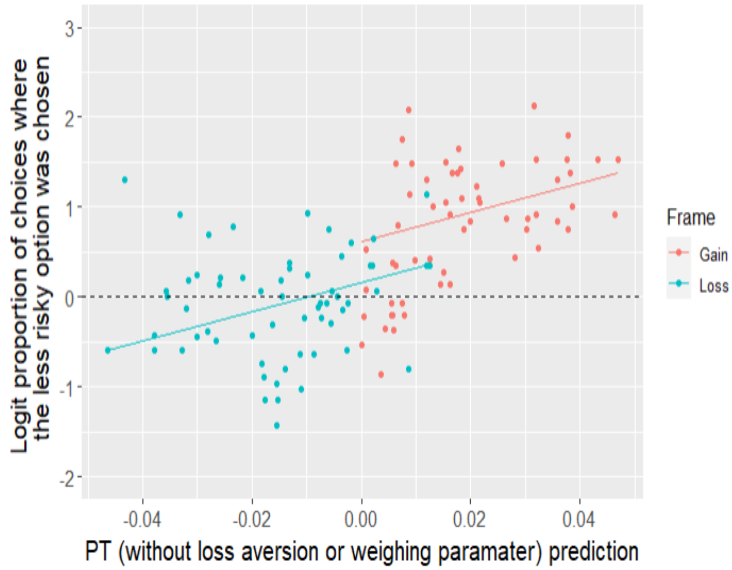
Model summaries for REP sample

Theory/Account	Theory coeff.	Frame coeff.	AIC	BIC	AUC
Model with no Theory variable	NA	1.00***	4560.7	4597.7	0.85
Prospect Theory Versions					
Full	1.61***	.81***	4550.2	4593.5	0.85
No Loss Aversion	1.92**	.82***	4555.0	4598.2	0.84
No weighting parameters	5.94**	.68***	4554.4	4597.6	0.85
No weighting parameters or Loss aversion	16.33***	.45**	4543.9	4587.1	0.85
Gist-based Accounts					
Fuzzy-Trace Theory	.45***	.57***	4536.5	4579.7	0.84
Fuzzy-Trace Theory +	.35***	.57***	4533.4	4576.7	0.84
Explicated Valence Account	.45***	.57***	4536.5	4579.7	0.84
Good/Bad Count	.23***	.88***	4548.0	4591.3	0.85
Sentiment Analysis	1.49***	.62***	4523.1	4566.3	0.84
Model with Prospect Theory (No weighting parameters or Loss aversion) & Sentiment Analysis	5.73, 1.31***	.48**	4523.4	4572.8	0.84

***p < .001, **p < .01 , *p < .05

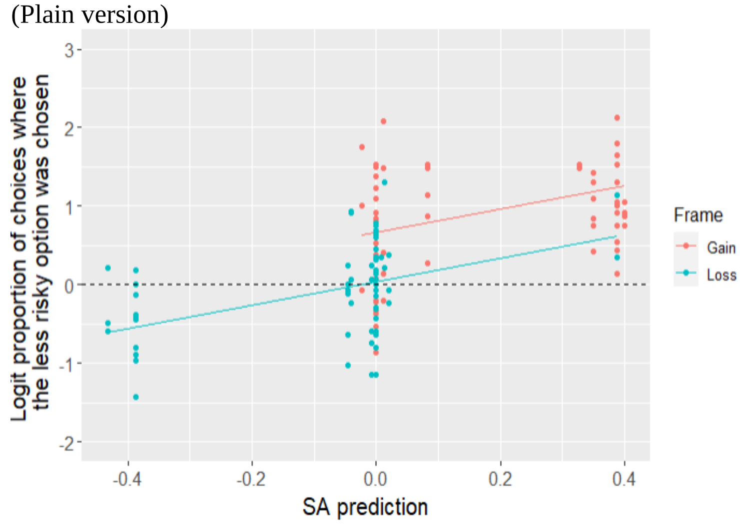


a. Prospect Theory with loss aversion and weighting parameters (Full version)



b. Prospect Theory without loss aversion and weighting parameters (Plain version)

c. Fuzzy-Trace Theory + (modified version of Fuzzy-Trace Theory)



d. Sentiment Analysis

Figure 5. Logit proportion of choices where the less risky option is chosen in the REP sample is plotted against the predictions of the specific theories for gain (orange) and loss (green) frame.

Model summaries for the REP sample for all nine theories appear in **Table 2**. *Figure 5* shows the results for four of the theories, with theory predictions on the X axis and a function of the proportion of choices where the less risky option is chosen on the Y axis. Each graph contains 120 points (15 comparisons x 2 frames x 4 domains). The model summaries for all the theories in the REP sample (**Table 2**) have a significant positive coefficient, which is also seen in the form of positive slopes in the 4 graphs shown in *Figure 5*. This positive value indicates that the theories explain some of the variation in choice proportions. Because predictions of different theories are on different scales, we cannot compare theory coefficients directly. However, there is always a residual framing effect which means that a significant proportion of framing is still unexplained by each of the theories. This is shown in the graphs in *Figure 5* as a difference between the lines for the frames.

Unaccounted variation shows up as scatter in the graphs of the theories. Hence, none of the theories is completely accurate. Area under the ROC curve (AUC) also tells us that the theories perform moderately well. All the models perform similarly in terms of AUC.

Looking at Akaike information criterion (AIC) and Bayesian information criterion (BIC) suggests that the theories are performing similarly. Sentiment Analysis has the lowest values for AIC and BIC, making it a relatively better fitting theory. The simplest version of Prospect Theory performs slightly better than the other versions (it also has the smallest residual framing effect), indicating that the non-linear weighting and loss aversion might be hurting the performance of the theory while predicting framing effects.

When we look at the model summaries from the MTurk sample (**Table 3**), we observe that Prospect Theory (without loss aversion or weighting parameters) performs best among the Prospect Theory versions and is the only theory model with a non-significant framing coefficient. It is followed closely by Fuzzy-Trace Theory +, Fuzzy-Trace Theory, and Explicated Valence Account from the Gist-based theories. Although these gist-based accounts have significant theory coefficients, there is still some residual framing, making them slightly worse than the simplest Prospect Theory. The AUC values for the MTurk sample are higher than those for the REP sample, indicating that the models perform better in the MTurk sample.

Table 3

Model summaries for MTurk sample

Theory/Account	Theory coeff.	Frame coeff.	AIC	BIC	AUC
Model with no Theory variable	NA	1.29***	4587.6	4625.0	0.90
Prospect Theory Versions					
Full	3.46***	.88***	4549.8	4593.5	0.90
No Loss Aversion	3.81***	.94***	4568.0	4611.7	0.89
No weighting parameters	15.52***	.47**	4550.7	4594.4	0.90
No weighting parameters or Loss aversion	32.97***	.19	4537.2	4580.9	0.90
Gist-based Accounts					
Fuzzy-Trace Theory	.78***	.56***	4537.5	4581.2	0.90
Fuzzy-Trace Theory +	.60***	.58***	4535.7	4579.4	0.90
Explicated Valence Account	.78***	.56***	4537.5	4581.2	0.90
Good/Bad Count	.38***	1.08***	4564.7	4608.4	0.90
Sentiment Analysis	1.63***	.88***	4550.7	4594.4	0.90
Model with Prospect Theory (No weighting parameters or Loss aversion) & Sentiment Analysis	25.12***, .96**	.21	4528.7	4578.6	0.90

***p < .001, **p < .01 , *p < .05

In some graphs, we observe more scatter in the loss frame (see *Figure 5*). We also created models containing the interaction effects between the frame and theory variables and obtained similar results for model fit. In general, slopes were more positive for gains than for losses. However, since our goal was to check the theory fit (not the model fit), we excluded interaction effects from our primary models. Because we have not included interaction terms in these models, the trendlines are parallel for the gains and losses.

Complications and Limitations

Fitting Prospect Theory. We speculated that using the standard parameters from Tversky and Kahneman's 1992 paper for Prospect Theory could be hurting model performance. For this reason we fit Prospect theory to the data using the cpt_d() function in R (Jarecki, 2020). Then, we used the new parameters (check the **Appendix**) to obtain Prospect Theory predictions for the various conditions, which unfortunately did not help model performance.

Riskiness order for problematic comparisons. The Prospect Theory version with no loss aversion or weighting parameters has a positive prediction in the loss frame for the comparisons *Somewhat-risky Mismatched vs. Somewhat-risky Matched* (2v3) and *Somewhat-risky zero-in-loss vs. Somewhat-risky zero-in-gain* (4v5) (see *Figure 5b*). This prediction that the less risky option will be preferred in the loss frame is counterintuitive.

Consider *Somewhat-risky Mismatched vs. Somewhat-risky Matched* (2v3) in the Cancer domain:

[Gain frame]

Somewhat-risky Mismatched option (2)*:* There is a 1/4 probability that 7,500 patients will be saved and a 3/4 probability that 2,300 patients will be saved.

Somewhat-risky Matched option (3)*:* There is a 2/5 probability that 6,300 patients will be saved and a 3/5 probability that 1,800 patients will be saved.

[Loss frame]

Somewhat-risky Mismatched option (2)*:* There is a 1/4 probability that 1,500 patients will die and a 3/4 probability that 6,700 patients will die.

Somewhat-risky Matched option (3)*:* There is a 2/5 probability that 2,700 patients will die and a 3/5 probability that 7,200 patients will die.

With these numbers, the simplest Prospect Theory predicts that the *Somewhat-Risky Mismatched* (less risky) option would be preferred by more people in the gain frame but also in the loss frame.

This counterintuitive prediction also occurs for the *Somewhat-risky zero-in-loss vs. Somewhat-risky zero-in-gain* (4v5) comparison. Other versions of Prospect Theory have positive predictions for some other conditions, but this positive prediction from the simplest Prospect Theory was especially surprising. It was unexpected since the value function should have shown a negative difference (risk-seeking) in the loss frame, no matter how small the magnitude in this version of the theory. Loss aversion and weighting parameters were 1, so they couldn't have caused a change in the sign of the prediction. The reason why the theory predicted this positive value is because when the two options are very close in riskiness, shifting to the loss frame gives different numbers resulting a change in the difference sign.

This raised a question about whether the riskiness order of the options in the gain frame was no longer applicable for the loss frame, which would imply that people found *Somewhat-risky Mismatched* (2) riskier than *Somewhat-risky Matched* (3) and *Somewhat-risky zero-in-loss* (4) riskier than *Somewhat-risky zero-in-gain* (5) in the loss frame.

To solve this ambiguity in the riskiness order for the loss frame, we implemented two solutions. First, we reversed the order of riskiness for the two options in the loss frame for both of these conditions, swapped the coding of the corresponding choices and predictions in the data, and ran the models on the new data. We would also have to think about whether it would be right to call it framing effect if the same option were chosen in both the frames (after reversing the riskiness order in the loss frame). Second, we dropped the 2v3 and 4v5 conditions and re-ran the models. Our models looked similar to our original models (Refer to **Appendix** for more details). Hence, we decided to stay with our original setup for our analysis.

Study Limitations

The types of options in our option pool were also limited. There are many other ways to create options to study framing effects (e.g., completing the sure option, truncating the risky option). Using a more diverse choice set could provide more insight into the strengths and weaknesses of the theories and inform the creation of a better theory to explain risky-choice decision making. Another limitation of this study is that it had a between-subjects design for the 15 conditions, which does not allow us to assess whether a theory (e.g., Prospect Theory) works better for some participants than for others. We are currently working on the within-subjects version of this study.

Conclusion

The current literature consists of multiple theories explaining risky-choice framing effects. We expanded the option set to include four types of somewhat-risky options and tested the theories to see how well they would generalize. A significant framing effect was observed in almost all of the conditions. Mixed models revealed that all the theories explained framing effects to some extent. However, there was still a residual framing effect and some unexplained variation in the data. Hence, none of the theories performed extremely well in predicting the participant choices. This research demonstrates that testing on a wide range of options reveals the shortcomings in the existing theories. The Prospect Theory version without loss aversion and weighting parameters performed better than the full Prospect Theory, indicating that these parameters hurt the performance of the theory with respect to framing effects, at least in our data. Since we see mixed results for the theories when we look at each of the conditions separately, we can logically conclude that people might implement different problem-solving strategies depending on the option pairs, instead of applying a general set of principles to all option comparisons. Hence, further research needs to be done with an even broader option pool or with another effect in risky-choice decision making to determine which strategies are applied by which people in what specific situations. This research will help in revising the current theories or coming up with a better theory to explain people's thought process when faced with a choice involving risk.

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Appendix

Domain Scenarios

Wildfire:

Imagine that the wildfire season is about to start and an old-growth forest in the Northwest of the U.S. will be affected. This forest is home to 6,000 animals that are endangered by the fire. Two programs have been proposed to protect the animals.

Drought:

Imagine that a severe drought is foreseen to hit the state of Missouri next summer. The drought will cause the destruction of 48,000 acres of crops. Two programs of water supply have been proposed.

Investment:

Imagine that John invested $72,000 in a company. The company's financial situation is in jeopardy, and so is John's investment. Two alternatives are available.

Option Construction

We considered the following probability values in the Gain frame: 1/5, 1/4, 1/3, 2/5, 1/2, 3/5, 2/3, 3/4, 4/5. For the four domains [Investment, Cancer, Drought, Wildfire] we used [1/3, 2/5, 1/2, 3/5] respectively as the probability of the ‘all’ outcome in the *Risky* option in the gain frame. This probability was assigned to the greater outcome in the *Somewhat-risky Matched* option. For the higher outcomes of the *Somewhat-risky Mismatched* and *Somewhat-risky zero-in-loss* options, we assigned the probability that was two steps lower in the list than the probability for the *Risky* option, i.e. [1/5, 1/4, 1/3, 2/5] respectively. For the *Somewhat-risky zero-in-gain* option, we went two steps above the probability for the *Risky* option, i.e. [1/2, 3/5, 2/3, 3/4] respectively. We assigned total magnitudes for each domain such that they were divisible by the probabilities of that domain [72000, 9000, 48000, 6000]. The *Risky* and *Somewhat-risky zero-in-gain* options had ‘0’ as the smaller outcome. The rest of the outcome values were filled so that the expected values of all the options was the same. For the Loss frame, we used the same probabilities but shifted outcomes from the Gain frame [Total magnitude – Corresponding Outcome of option].

Table 4

Model summaries for REP sample with 13 out of 15 conditions (without 2v3 and 4v5)

Theory/Account	Theory coeff.	Frame coeff.	AIC	BIC	AUC
Model with no Theory variable	NA	1.03***	4256.6	4293.2	0.85
Prospect Theory Versions					

Full	1.54**	.83***	4248.4	4291.2	0.85
No Loss Aversion	2.23**	.82***	4249.3	4292.0	0.84
No weighting parameters	5.02*	.75***	4253.3	4296.0	0.85
No weighting parameters or Loss aversion	15.03***	.50**	4244.1	4286.8	0.85
Gist-based Accounts					
Fuzzy-Trace Theory	.45***	.59***	4235.4	4278.2	0.84
Fuzzy-Trace Theory +	.35***	.59***	4232.4	4275.2	0.84
Explicated Valence Account	.45***	.59***	4235.4	4278.2	0.84
Good/Bad Count	.22***	.91***	4245.6	4288.3	0.85
Sentiment Analysis	1.36***	.67***	4228.1	4270.8	0.85
Model with Prospect Theory (No weighting parameters or Loss aversion) & Sentiment Analysis	5.30, 1.20***	.53**	4228.7	4277.6	0.85

***p < .001, **p < .01 , *p < .05

Table 5

Model summaries for REP sample with coding reversal for 2v3 and 4v5

Theory/Account	**Theory coeff.**	**Frame coeff.**	**AIC**	**BIC**	**AUC**
Model with no Theory variable	NA	1.09***	4544.0	4581.1	0.85
Prospect Theory Versions					
Full	1.54**	.85***	4537.8	4581.0	0.85
No Loss Aversion	2.20**	.84***	4538.2	4581.4	0.84
No weighting parameters	2.88	.93***	4544.6	4587.8	0.85
No weighting parameters or Loss aversion	12.79**	.64***	4536.5	4579.7	0.85
Gist-based Accounts					
Fuzzy-Trace Theory	.44***	.62***	4526.0	4569.3	0.85

Fuzzy-Trace Theory +	.34***	.64***	4523.4	4566.6	0.85
Explicated Valence Account	.44***	.62***	4526.0	4569.3	0.85
Good/Bad Count	.21***	.95***	4534.4	4577.7	0.84
Sentiment Analysis	1.37***	.71***	4515.5	4558.7	0.84
Model with Prospect Theory (No weighting parameters or Loss aversion) & Sentiment Analysis	2.90, 1.29***	.63***	4517.1	4566.5	0.85

***p < .001, **p < .01 , *p < .05

Parameters for the fitted Cumulative Prospect Theory

We standardized the stimuli for each domain by dividing the outcomes with the respective total magnitudes. Then we fitted Cumulative Prospect Theory to our data from the REP sample providing the stimuli to the cpt_d() function (Jarecki, 2020). The parameter values we obtained were power for gains = .737, power for losses = .001, probability weighting for gains = .945, probability weighting for losses = 1.145, and loss aversion = .030.

Theory/Account	Theory coeff.	Frame coeff.	AIC	BIC	AUC
Fitted Prospect Theory Model	.21*	.81***	4556.5	4599.7	0.85

***p < .001, **p < .01 , *p < .05

The parameters for gains are sensible and consistent with standard Prospect Theory values. However, the parameters for losses (e.g., for loss aversion) make much less sense. The very low exponent (.001) yields a value function that is essentially horizontal in losses.